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Management and spatial resolution effects on yield and water balance at regional scale in crop models

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► To cite this version:

Julie Constantin, Helene Raynal, Eric Casellas, Holger Hoffman, Marco Bindi, et al.. Management and spatial resolution effects on yield and water balance at regional scale in crop models. *Agricultural and Forest Meteorology*, 2019, 275, pp.184 - 195. 10.1016/j.agrformet.2019.05.013 . hal-02620098

HAL Id: hal-02620098

<https://hal.inrae.fr/hal-02620098v1>

Submitted on 29 Aug 2023

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27 **Abstract**

28 Due to the more frequent use of crop models at regional and national scale, the effects of spatial data input
29 resolution have gained increased attention. However, little is known about the influence of variability in crop
30 management on model outputs. A constant and uniform crop management is often considered over the simulated
31 area and period. This study determines the influence of crop management adapted to climatic conditions and input
32 data resolution on regional-scale outputs of crop models. For this purpose, winter wheat and maize were simulated
33 over 30 years with spatially and temporally uniform management or adaptive management for North Rhine-
34 Westphalia (~34 083 km²), Germany. Adaptive management to local climatic conditions was used for 1) sowing
35 date, 2) N fertilization dates, 3) N amounts, and 4) crop cycle length. Therefore, the models were applied with four
36 different management sets for each crop. Input data for climate, soil and management were selected at five
37 resolutions, from 1×1 km to 100×100 km grid size. Overall, 11 crop models were used to predict regional mean
38 crop yield, actual evapotranspiration, and drainage. Adaptive management had little effect (<10 % difference) on
39 the 30-year mean of the three output variables for most models and did not depend on soil, climate, and
40 management resolution. Nevertheless, the effect was substantial for certain models, up to 31 % on yield, 27 % on
41 evapotranspiration, and 12 % on drainage compared to the uniform management reference. In general, effects
42 were stronger on yield than on evapotranspiration and drainage, which had little sensitivity to changes in
43 management. Scaling effects were generally lower than management effects on yield and evapotranspiration as
44 opposed to drainage. Despite this trend, sensitivity to management and scaling varied greatly among the models.
45 At the annual scale, effects were stronger in certain years, particularly the management effect on yield. These
46 results imply that depending on the model, the representation of management should be carefully chosen,
47 particularly when simulating yields and for predictions on annual scale.

48

49 **Keywords:** drainage, evapotranspiration, aggregation, decision rules, scaling

50 1. Introduction

51 Large-scale assessment studies based on simulations by crop models are frequently used to evaluate the impacts
52 of agriculture. These studies usually focus on predictions of crop production in different contexts, such as climate
53 change, its inter-annual variability, or trends over time (Gaiser et al., 2010; Nendel et al., 2013). Crop models are
54 also used to study carbon sequestration or the greenhouse gas balance at regional or national scale (Gaiser et al.,
55 2009, 2008; Tornquist et al., 2009). Other studies focus on the water balance and its dynamics at the watershed
56 scale. For the latter, crop models are combined with other models (e.g., hydrological) and applied to quantitative
57 water management and irrigation issues (Noory et al., 2011; Robert et al., 2018; Therond et al., 2014).

58 Crop models are useful tools for large-scale assessment since exhaustive measurements are not feasible or
59 available. However, they were developed to simulate homogeneous fields, each represented by a combination of
60 one soil and one climate. Some of these models were designed to simulate only one season, e.g. one crop and its
61 management, while others are capable of simulating different crops in sequence, mimicking a crop rotation over a
62 longer time period (Kollas et al., 2015). When applied at a larger scale, these models are usually applied in a
63 gridded approach, simulating each grid cell independently, while assuming homogeneity within each grid cell (De
64 Wit et al., 2012; Huang et al., 2015; Mo et al., 2005; van Ittersum et al., 2013). For such approach, it is necessary
65 to provide input data for soil, climate, and management for each simulated unit. Depending on the study and the
66 systems' heterogeneity, the number of homogeneous units can range from a few to millions. Such data, especially
67 management data, are not easily available at large scales and at high spatial or temporal resolution. Several
68 methods exist to scale-up the data over the whole study area, such as sampling, aggregation from fine to coarser
69 resolution, extrapolation or interpolation of the available data (Ewert et al., 2011). As an alternative, management
70 information can also be simulated for large-scale studies (Hutchings et al., 2012).

71 Nowadays, it is possible to obtain soil and climate data at a relatively high resolution and at a large or even global
72 scale from databases such as those in the Global Soil Map project (<http://globalsoilmap.net/>), the European soil
73 portal for soil, the SoilGrids project (soilgrids.org) and the international CORDEX initiative for climate projection
74 (<https://www.euro-cordex.net/>). On the other hand, the available databases on crop management data are at
75 coarser resolutions such as those reported by Portmann et al. (2010) and Sacks et al. (2010) for crop growing
76 periods or earthstat.org for fertilizer inputs. Usually, the few data available on crop management come from

77 interviews with farmers, local experts, or observation networks. It provides an average date of sowing, harvest, and
78 fertilization for instance or fertilizer input amounts for a given region for different crops and generally concern only
79 one or a few years. Some initiatives such as the observation network of the German weather service DWD
80 documenting key phenological stages as well as sowing and harvest could provide useful data for regional
81 modelling (Kersebaum and Nendel, 2014) but do not cover the wide range of cultivation operations such as nitrogen
82 fertilization for instance. As a result, large-scale studies usually consider management as uniform across the region
83 and fixed over multiple years. However, it is well known that crop management, such as sowing, varies over space
84 and time (Leenhardt and Lemaire, 2002). Additionally, the sowing date significantly impacts crop development and
85 yield (Bonelli et al., 2016), and influences subsequent management actions during season.

86 To address the scarcity of the data and to adapt the management to the local and annual conditions, some authors
87 suggested using management rules. Such management rules aim at reproducing the behavior of farmers and their
88 crop management strategies (Maton et al., 2005; Nendel, 2009; Senthilkumar et al., 2015). In addition, these rules
89 would help identify better management strategies. For example, suitable climate and soil conditions could be
90 identified to perform cultivation operations (e.g., avoiding soil compaction by triggering an operation when the soil
91 is not too wet or avoiding the risk of frost for spring crops). This adaptive management, based on management
92 decision rules, could have a strong impact on model outputs but is rarely investigated at a large scale. Since the
93 impact of input data aggregation and adaptive management can differ according to the output variables and crop
94 models, these effects should be investigated with respect to a range of different crop models, output variables, and
95 cultivation operations (i.e. sowing, soil tillage, irrigation...).

96 The objective of this study was to analyze the effect of adaptive management and spatial resolution on regional
97 yields, evapotranspiration, and drainage predicted by a set of crop models. The main issues addressed were (1)
98 whether adaptive management and/or input resolution influence the crop models' outputs at the regional scale, in
99 which way and how much and (2) whether the scaling effect varies when management changes over time and
100 space.

101 To meet this goal, we quantified the impact of adaptive management and input resolution on the regional mean of
102 simulated yield, evapotranspiration, and drainage for each individual year as well as for the 30-year average. We
103 further analyzed whether the impact of management or spatial resolution depended on the crop model, output of

104 interest, crop, or cultivation operation. To do so, we introduced adaptive management for sowing dates, fertilization
105 dates, and crop maturity classes based on decision rules and variable amounts of nitrogen fertilization.

106 **2. Materials and Methods**

107 **2.1. Study area**

108 The study area was the 34.083 km² federal state of North Rhine-Westphalia (NRW, 6.0-9.5° E, 50.0-52.5° N),
109 located in the west of Germany. NRW has a temperate and humid climate with an oceanic influence. Like Hoffmann
110 et al. (2016b) and Zhao et al. (2015), we assumed in the simulations that agricultural land covered the entire region
111 and that winter wheat and silage maize were the two dominant monoculture crops. Over the period studied (1982-
112 2012), mean annual temperature was 9.7 °C, mean annual precipitation was 899 mm, and mean annual global
113 radiation was 3.758 MJ m⁻².

114 **2.2. Crop models**

115 We selected 11 crop models to run the simulations from 1982-2012: AgroC (Herbst et al., 2008; Klosterhalfen et
116 al., 2017), APSIM-Nwheat (Asseng et al., 2000), CoupModel (Conrad, 2009; Jansson, 2012), DailyDayCent (Del
117 Grosso et al., 2006; Yeluripati et al., 2009), EPIC (Williams, 1995; Williams et al., 1983), Expert-N (Priesack et al.,
118 2006), HERMES (Kersebaum, 2007), LINTUL in the framework solution SIMPLACE<Lintul5, SLIM> (Gaiser et al.,
119 2013; Zhao et al., 2015b), MCWLA (Tao et al., 2009; Tao and Zhang, 2013), MONICA (Nendel et al., 2011) and
120 STICS within the RECORD platform (Bergez et al., 2014; Brisson et al., 2003). These process-based models run
121 at a daily time step, except for Expert-N, which runs at an hourly time step. The models represent soil and crop
122 processes with differing degrees of simplification. All simulated winter wheat, but only seven simulated silage maize
123 in this paper. All represent water and nitrogen stresses, except for AgroC and MCLWA, which represent only water
124 stress.

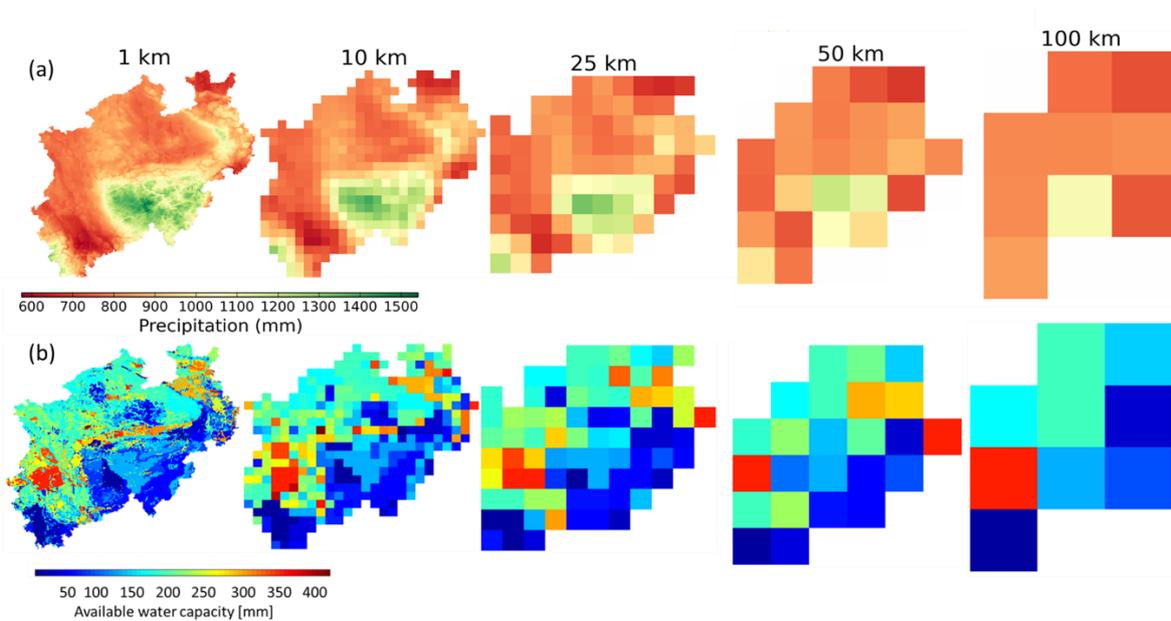
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126 **2.3. Input data of the crop models**

127 **2.3.1. Climate and soil data aggregation**

128 For climate, we used 30 years of daily weather for 34.168 grid cells of 1×1 km resolution and aggregated these
129 data for the 10×10, 25×25, 50×50, and 100×100 km grid cells, as described by Hoffmann et al. (2015). For soil

130 data, we used the dominant soil of the 1×1 km grid cells to set the soil type for the 10×10, 25×25, 50×50, and
 131 100×100 km grid cells, respectively. For the soil and climatic data, see Hoffmann et al. (2016a) and for more details
 132 of data aggregation, see Hoffmann et al. (2016b). Figure 1 presents the maps of mean annual precipitation and
 133 available water capacity (soil water content at field capacity minus the soil water content at wilting point) of the soils
 134 for each resolution.



135
 136 **Figure 1.** Maps of (a) mean annual precipitation over 30 years (1982-2012) and (b) available water capacity in each of the five resolutions
 137 for North Rhine-Westphalia, Germany. All simulations were run using the same resolution of soil and climate data (km×km):
 138 1×1, 10×10, 25×25, 50×50, and 100×100.

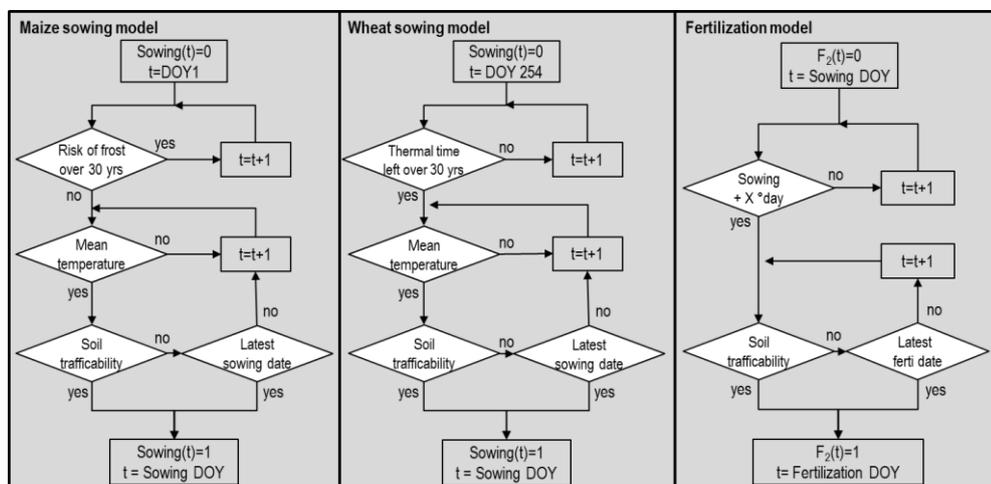
139 2.3.2. Crop choice and management sets

140 We simulated the two dominant crops of the region in monoculture in continuous model runs of 30 years on every
 141 grid cell. Both winter wheat and silage maize were grown under rainfed conditions and with mineral N fertilization
 142 (208 and 238 kg N ha⁻¹ yr⁻¹, respectively). For both crops, we simulated export of crop residues at harvest and
 143 plowing of soil in autumn. We simulated six sets of management strategies to analyze the impact of adaptive
 144 management in interaction with the scaling effect:

- 145 1. M_{fix} is the reference, which is the same uniform management for a given crop regardless of the year or
 146 grid cell. We used the common cultivation operations in NRW as the reference management strategy.
 147 Winter wheat and silage maize were sown on 1st of October and 20th of April, respectively. Crops were

148 harvested at maturity or on 1st of August for wheat and 20th of September for maize, depending on the
 149 model.

150 2. *Ms* uses variable sowing, fertilization, and harvest dates for each cell, at each resolution and year
 151 according to decision rules based on climate, as in Senthilkumar et al. (2015) for maize and Savin et al.
 152 (2007) for wheat. For each crop, we calculated the earliest sowing date for all 30 years per grid cell (Fig.
 153 2). Then, beginning on this date each year for each grid cell, we checked whether daily temperature and
 154 soil trafficability exceeded thresholds necessary for sowing. If all conditions were met, the crop was sown
 155 on that day. If sowing was impossible before a latest “allowed” date, it occurred on this date.



156
 157 **Figure 2.** Overview of decision rules for wheat and maize sowing and fertilization dates. DOY = day of year

158
 159 Fertilization date was set from the sowing date and depended on a minimum amount of thermal time and
 160 sufficient soil trafficability. Like for sowing, we defined a latest “allowed” date. We calculated the earliest
 161 harvest date as the number of days required to reach a certain cumulative thermal time from the sowing
 162 date. Beginning on this date, we checked soil trafficability each day to identify the first suitable harvest
 163 date. We calibrated the thresholds used in the decision rules to ensure that average dates were similar to
 164 those in M_{fix} . Estimated sowing dates among all grid cells and years ranged from 12th of March to 11th of
 165 May for maize and 21st of September to 16th of December for winter wheat. When averaged for all cells in
 166 the region, the mean sowing date each year ranged from 13th of April to 30th of April for maize and 22nd of
 167 September to 25th of October for wheat over the 30 years. Median sowing dates over the 30 years were
 168 19th of April and 4th of October for maize and wheat, respectively, which were similar to those of M_{fix} (20th
 169 of April and 1st of October). Distributions of regional sowing dates for the five resolutions were similar,

170 despite some differences for the coarser resolutions. Depending on the year, the mean regional sowing
171 date was similar among resolutions.

172 3. $M_{s_{var}}$ is similar to the M_s approach, but with the maturity class of the cultivar adapted to the climate
173 conditions in each grid cell on each resolution. We chose one of three maturity classes or varieties (early,
174 middle, or late) with a development length better adapted to climate characteristics by calculating the mean
175 cumulative thermal time between sowing dates and the mean harvest date (20th of September for maize
176 and 10th of July for wheat) over the 30 years. The maturity class in a given cell remained the same for all
177 30 years. We calibrated the three varieties for each model using the sowing and harvest dates of ten
178 contrasting cells.

179 4. The fourth to sixth sets are the same as the M_s approach, but with a decrease in mineral N fertilization by
180 25% (M_{SF75}), 50% (M_{SF50}), and 75% (M_{SF25}) of the reference fertilization amount, respectively. Thus,
181 mineral N fertilization decreased from 238 to 179, 119 and 60 kg N ha⁻¹ yr⁻¹ for maize and from 208 to 156,
182 104 and 52 kg N ha⁻¹ yr⁻¹ for wheat in M_{SF75} , M_{SF50} , and M_{SF25} , respectively.

183 The objective of these six sets was to create spatial and temporal variability in the cultivation operations to analyze
184 their impacts on the model results. The adaptive management based on climatic conditions was calculated for each
185 grid cell for each of the five resolutions. The purpose was not to reproduce the actual management strategies, but
186 to reproduce a credible range of cultivation operations over time and within the region to analyze their potential
187 impacts on model outputs. Other cultivation operations such as tillage were assumed spatially and temporally
188 uniform for all management sets.

189 **2.3. Simulation overview and data selection**

190 We analyzed three output variables: crop yield and two components of the water balance, evapotranspiration over
191 the growing period and annual drainage under wheat to determine if some model outputs were more sensitive to
192 scaling or management than others. Yield is often studied at large scale, while water fluxes are quite important
193 when crop models are coupled with hydrological models to analyze water management at the watershed scale. We
194 first selected and summarized simulated data (Table 1). We analyzed all three variables for five models only but
195 yield and evapotranspiration were provided for six other models. Due to the complexity of the simulated experiments
196 and model limitations, not all simulations were performed with all models (Table 1).

197

198 **Table 1.** Overview of the simulated resolutions and outputs analyzed by model, crop and management set.

Model	Code	Outputs	Resolution for Wheat						Resolution for Maize					
			M _{fix} ^a	Ms	Ms _{var}	Ms _{F75}	Ms _{F50}	Ms _{F25}	M _{fix}	Ms	Ms _{var}	Ms _{F75}	Ms _{F50}	Ms _{F25}
MONICA	MONI	Y, E, D ^b	All ^c	All	All	All	All	All	All	All	All	All	All	All
STICS	STIC	Y, E, D	All	All	All	All	All	All	All	All	All	All	All	All
LINTUL	LINT	Y, E, D	All	All	-	All	All	All	All	All	All	All	All	All
CoupModel	COUP	Y, E, D	All	All	-	All	All	All	-	-	-	-	-	-
Expert-N	EXPN	Y, E, D	-	All	All	All	All	All	-	-	-	-	-	-
EPIC	EPIC	Y, E	All	All	All	All	All	All	All	All	All	All	All	All
HERMES	HERM	Y, E	All	All	All	All	All	All	All	All	All	All	All	All
DailyDayCent	DayC	Y, E	All	All	All	All	All	Not 1x1 ^d	All	All	All	Not 1x1	All	Not 1x1
APSIM-Nwheat	NWHE	Y, E	Not 1x1	All	All	All	All	All	-	-	-	-	-	-
AgroC^e	AGRC	Y, E	All	All	All	-	-	-	All	All	All	-	-	-
MCWLA	MCLW	Y, E	All	All	All	-	-	-	-	-	-	-	-	-

199 ^a M_{fix} is a fixed management strategy for each crop; Ms indicates that sowing and fertilization dates depend on the grid cell and the year;
200 M_{Svar}, M_{SF50} and M_{SF25} are the same as Ms but with adaptation of cultivar precocity to the cell or with a 50% and 75%, decrease in fertilization,
201 respectively.

202 ^b Y is yield; E is actual evapotranspiration over the growing season for both crops; D is annual water drainage under wheat.

203 ^c "All" indicates that all resolutions (1x1 km, 10x10 km, 25x25 km, 50x50 km and 100x100 km) were simulated

204 ^d "Not 1x1" indicates that all resolutions except for 1x1 km were simulated.

205 ^e Data for E in AgroC are for maize only.

206

207 The simulations were done for the five resolutions (1x1, 10x10, 25x25, 50x50, and 100x100 km) with the same
208 resolution for soil, climate, and management inputs. Among the six different management sets (M_{fix}, Ms, Ms_{var},
209 Ms_{F75}, Ms_{F50}, and Ms_{F25}), the uniform one (M_{fix}) was the same over all resolutions, while the others based on decision
210 rules were generated at the same resolution as soil and climatic inputs. This resulted in a maximum of 30
211 combinations for each crop (five resolutions for each of the six management sets).

212 Scaling and management effects were studied on outputs averaged at the regional scale. Scaling effect was defined
213 as the difference on the output of interest when using coarser resolution inputs in a model. Management effect was
214 defined as the difference on the output of interest when using different management inputs in a model.

215

216 2.4. Data analysis

217 We quantified management and scaling effects on the regional means for each year of the 30-year simulation and
218 for all 30 years together by model, crop and output variable. To analyze the scaling effect, we calculated the
219 difference between the output at each resolution (\bar{X}_{Sx}) and those simulated at the highest resolution available
220 (\bar{X}_{Sr}):

$$221 \Delta \bar{X}_S = \frac{\bar{X}_{Sx} - \bar{X}_{Sr}}{\bar{X}_{Sr}} \times 100 \quad [1]$$

222 where $\Delta\bar{X}_S$ is the difference (%) in the output at a given resolution compared to that at the reference resolution,
223 \bar{X}_{Sx} is the mean output for the region at a given resolution, and \bar{X}_{Sr} is the mean output of the region at the reference
224 resolution, which was the 1×1 km resolution, except for APSIM-Nwheat in M_{fix} and DailyDayCent in Ms_{F25} and Ms_{F75}
225 for which it was 10×10 km. We calculated this difference due to input resolution by crop, model, and management
226 set for each resolution, except the reference set.

227 To analyze the management effect, we calculated the difference between the output for each management set
228 (\bar{X}_{Mx}) and those simulated for the reference set (\bar{X}_{Mr}):

$$229 \quad \Delta\bar{X}_M = \frac{\bar{X}_{Mx} - \bar{X}_{Mr}}{\bar{X}_{Mr}} \times 100 \quad [2]$$

230 where $\Delta\bar{X}_M$ is the difference (%) in the output for a given management set compared to that for the reference set,
231 \bar{X}_{Mx} is the mean output for the region for a given management set x , and \bar{X}_{Mr} is the mean regional output for the
232 reference management set, which was M_{fix} , except for Expert-N, for which it was Ms . We calculated this difference
233 resulting from adaptive management by crop, model, and resolution for each management set, except for the
234 reference set.

235 For analyses at the annual scale, we calculated an annual scaling effect (ASE) and annual management effect
236 (AME) for each of the 30 years, following the same logic as that for the 30-year mean (Eq. 1 and 2), but applied to
237 the annual regional mean of each model. Again, we calculated these differences by model, crop, output, and
238 resolution for AME or management set for ASE.

239 To determine if the effects of management or scaling were significant, we used a Student's t -test to compare each
240 regional mean for a given output to the result of its reference (1×1km for scaling and M_{fix} for management in most
241 cases). The comparison was done on both annual and 30-years means for each model, crop, and output.

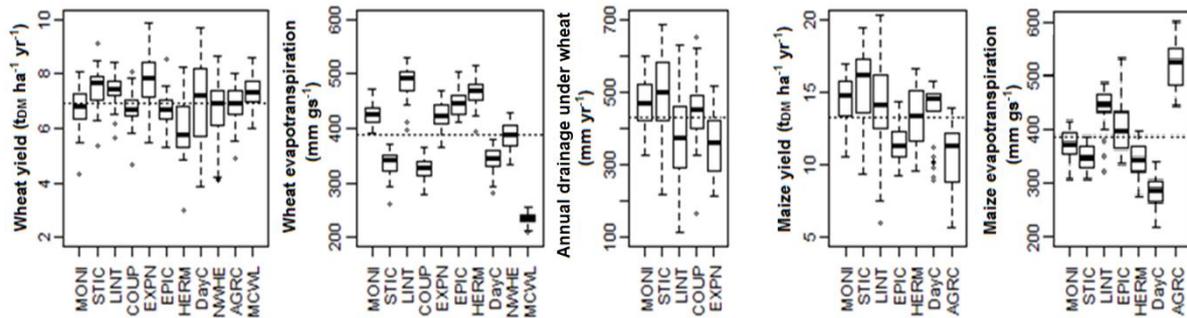
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243 **3. Results**

244 **3.1 Simulated yield, evapotranspiration, and drainage for winter wheat and silage maize**

245 Predictions of the regional annual yield, evapotranspiration, and drainage for the two crops differed among models
246 for M_{fix} at 1×1 km resolution. This difference was particularly large for evapotranspiration for both crops, with
247 regional annual medians by model ranging from 236-477 mm (235-484 mm for means) over the wheat growing

248 season and 285-527 mm (284-523 mm for means) over the maize growing season, resulting in a maximum
 249 difference of 334 and 239 mm, respectively (Fig. 3). Regional annual median wheat yield varied less among models,
 250 from 5.8-8.0 t ha⁻¹ (6.0-7.9 t ha⁻¹ in mean), while median maize yield ranged from 11.3-16.2 t ha⁻¹ (10.4-15.5 t ha⁻¹
 251 in mean). Median drainage varied from 356-500 mm yr⁻¹ (355-497 mm yr⁻¹ in mean) resulting in a maximum
 252 difference of 144 mm among the five models providing simulated drainage.



253
 254 **Figure 3.** Distributions of the region's annual means of yield (dry matter (DM); t_{DM} ha⁻¹ yr⁻¹) and evapotranspiration (growing season (gs);
 255 mm gs⁻¹) for wheat and maize, and annual mean drainage (mm yr⁻¹) under wheat over 30-year simulations by each model at its reference
 256 resolution (1 km × 1 km, except for NWHE (10 km × 10 km)) and management set (*M_{fix}*, except for EXPN (*M_s*)). The dotted line indicates
 257 the ensemble mean of all models for a given output. See Table 1 for model abbreviations.

258 Inter-annual variability also varied among the models (Fig. 3). For instance, LINTUL predicted highest inter-annual
 259 variability in maize yield, while EPIC predicted lowest variability. A similar difference was observed for wheat yield
 260 between DailyDayCent (highest) and MCWLA (lowest), and for annual drainage between MONICA (highest) and
 261 STICS (lowest).

262 3.2 Management effect on 30-year regional means at each resolution

263 We analyzed the management effect on 30-year regional means by comparing *M_s*, *M_{s_{var}}* and *M_{s_{F75}}* to *M_{fix}* at each
 264 resolution. Maximum management effects (in negative and positive) in yield, evapotranspiration, and drainage
 265 among models were -26% and +31%, -27% and +15%, and -12% and +1%, respectively (Table 2). For yield, these
 266 maximum management effects were similar for wheat and maize. For evapotranspiration, maximum positive
 267 differences (overestimation as compared to the reference) were slightly higher for wheat (+14%) than for maize
 268 (+4%). For maize evapotranspiration, the difference tended to be negative (underestimation as compared to the
 269 reference), whereby this trend was less consistent for wheat evapotranspiration. For drainage, the use of adaptive
 270 management sets tended to result in a negative difference (underestimation) that was the same within all

271 resolutions, but one that was smaller than those for yield or evapotranspiration. However, the number of crop
 272 models reporting simulated drainage was much smaller as those reporting yield or evapotranspiration.

273 **Table 2.** Maximum negative and positive management effect among models ($Min(\Delta\bar{X}_M)$; $Max(\Delta\bar{X}_M)$) for the sets M_s , M_{svar}
 274 and M_{s75} compared to M_{fix} and number of models in each level of absolute effect ($|\Delta\bar{X}_M|$) for a given output averaged over
 275 the region and all 30 years. The results are shown by crop and resolution (1 km x 1 km to 100 km x 100 km).

		Wheat					Maize					All crops	
		1x1	10x10	25x25	50x50	100x100	1x1	10x10	25x25	50x50	100x100	All Res	
Maximum negative and positive effect (%)	Y ¹	$Min(\Delta\bar{X}_M)$	-20	-18	-19	-19	-24	-18	-19	-20	-21	-26	-26
		$Max(\Delta\bar{X}_M)$	18	19	20	31	20	23	24	20	20	20	31
	E ²	$Min(\Delta\bar{X}_M)$	-22	-23	-23	-24	-24	-21	-22	-23	-24	-27	-27
		$Max(\Delta\bar{X}_M)$	14	14	14	15	15	4	4	7	3	3	15
	D ³	$Min(\Delta\bar{X}_M)$	-12	-12	-12	-12	-12						-12
		$Max(\Delta\bar{X}_M)$	0	0	1	1	1			NA			1
Number of models by management effect level	Y	$ \Delta\bar{X}_M \leq 5\%$	4	5	5	5	6	0	0	0	0	0	25
		$5\% < \Delta\bar{X}_M \leq 10\%$	2	3	3	2	2	1	0	0	1	2	16
		$10\% < \Delta\bar{X}_M \leq 15\%$	1	1	1	0	0	2	4	4	3	2	18
		$15\% < \Delta\bar{X}_M \leq 20\%$	3	2	2	3	2	3	2	1	2	1	21
		$20\% < \Delta\bar{X}_M \leq 30\%$	0	0	0	0	1	1	1	2	1	2	8
		$30\% < \Delta\bar{X}_M \leq 40\%$	0	0	0	1	0	0	0	0	0	0	1
		Total	10	11	11	11	11	7	7	7	7	7	89
	E	$ \Delta\bar{X}_M \leq 5\%$	5	5	6	6	6	2	2	3	3	3	41
		$5\% < \Delta\bar{X}_M \leq 10\%$	2	2	1	0	1	2	2	1	1	1	13
		$10\% < \Delta\bar{X}_M \leq 15\%$	1	2	1	1	0	1	1	1	1	1	10
		$15\% < \Delta\bar{X}_M \leq 20\%$	0	0	0	1	2	1	1	1	1	1	8
		$20\% < \Delta\bar{X}_M \leq 30\%$	1	1	2	2	1	1	1	1	1	1	12
		Total	9	10	10	10	10	7	7	7	7	7	84
D	$ \Delta\bar{X}_M \leq 5\%$	4	4	4	4	4						20	
	$10\% < \Delta\bar{X}_M \leq 15\%$	1	1	1	1	1			NA			5	
	Total	5	5	5	5	5						25	

276 ¹ Y is crop yield

277 ² E is evapotranspiration over the growing season

278 ³ D is drainage over the growing season

279

280 The response of outputs to management adaptations was model-dependent (see Table S1). For wheat, certain
 281 models had low sensitivity to management sets, such as CoupModel, Expert-N, and STICS for all outputs ($|\Delta\bar{X}_S|$
 282 $\leq 6\%$) and LINTUL for yield and evapotranspiration. Other models were much more sensitive to changes in
 283 management, such as HERMES, AgroC, and DailyDayCent for crop yield, MCWLA and EPIC for
 284 evapotranspiration, and LINTUL for drainage. Overall, most predictions were similar to those with M_{fix} ($|\Delta\bar{X}_S| = 0$ -
 285 5%), although, some models predicted a large difference in the model output for certain management sets. This
 286 range of absolute difference below 5% was most common for most outputs, except for maize yield, for which the
 287 most common range of absolute difference was 10 to 15%. The regional yield for maize appeared more sensitive
 288 to differences in management than that for wheat, while the same range of differences was observed for
 289 evapotranspiration between the two crops. This higher sensitivity for maize was not related to a particular

290 management set, since each one (Ms , Ms_{var} , Ms_{F75}) could reach the same range of absolute difference, depending
 291 on the model.

292 The management effect on the 30-year regional mean was similar among resolutions for a given crop and output
 293 for most models (see Table S1). Therefore, resolution did not seem to influence the difference due to management,
 294 except for APSIM-Nwheat at 50×50 km resolution for both wheat yield and evapotranspiration, and for MCWLA at
 295 a resolution of 10×10 km and coarser for wheat evapotranspiration.

296 **Table 3.** Statistical analysis by model, crop and output of the management and scaling effect. Significant difference (** p-
 297 value <0.05) were tested by Student's t-Test compared to the reference. The number of model with significant effect and the
 298 total number of model available are given at the bottom of the table.

	Management effect															Scaling effect																					
	Wheat									Maize						Wheat						Maize															
	Ms			Msvar			MsF75			MsF50			MsF25			r10		r25		r50		r100		r50		r100											
	Yd	ET	Dr	Yd	ET	Dr	Yd	ET	Dr	Yd	ET	Dr	Yd	ET	Dr	Yd	ET	Yd	ET	Yd	ET	Yd	ET	Yd	ET	Yd	ET										
MONI	(p,a)			(p)	(p,a)		(p)	(p,a)		(p,a)	(p)		(p,a)	(p,a)		(p,a)	(p)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p)			(p)										
STIC	(p)	(p)		(p)	(p,a)		(p)	(p)		(p,a)	(p)		(p)	(p,a)		(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p)			(p)			(p)									
COUP	(p)			-	-					(p)			(p,a)	-										(p)			(p)										
LINT	(p)		(p)	-	-		(p)	(p)		(p)	(p)		(p,a)	(p,a)	(p)	(p)		(p)	(p)	(p,a)	(p)	(p,a)	(p)				(a)										
EPIC	(p)	(p,a)	-	(p)	(p,a)		(p)	(p,a)	-	(p,a)	(p,a)	-	(p,a)	(p,a)	-	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	(p,a)	-			-										
EXPN	-	-	-				(p)			(p)			(p)	(p)										(p)			(p)										
HERM	(p,a)	(p,a)	-	(p,a)	(p,a)		(p,a)	(p,a)	-	(p)	(p,a)	-	(p,a)	(p,a)	-	(p)		(p,a)	(p,a)	(p,a)		(p,a)		-			-										
DayC	-						(p,a)			(p,a)			(p,a)							(p,a)		(p,a)		(p)			(p,a)										
NWHE	(p,a)	-		(p,a)			(p,a)	-		(p,a)	-		(p,a)	-										-			(p)	(p,a)									
AGRC	(p,a)	-	-	(p,a)	-								(p,a)	(p,a)		(p,a)	(p,a)	-	-	-	-	-	-	-	-	-	-	-	-	-							
MCWL	(p)	(p,a)	-	(p)	(p,a)																			-			-										
nb(p,a)	7-2	7-5	1-0	6-2	7-6		7-2	5-4	1-0	8-4	5-3	1-0	8-7	8-5	1-0	6-3	4-4	6-6	6-4	5-5	4-3	6-6	4-3	6-6	4-3	2-0	1-0	4-0	2-1	4-0	1-1	3-2	4-2	0-2	1-1	0-2	1-0
Total	10	9	4	9	8		9	9	5	9	9	5	9	8	5	7	7	7	7	6	6	6	6	6	6	5	11	5	10	5	11	10	5	7	7	7	7

299 "Yd" is yield, "ET" is evapotranspiration over the growing season and "Dr" is the annual drainage. "p" means that the 30-years mean is significantly different
 300 from the reference. "a" means that the annual mean is significantly different from the reference "-" means the outputs was not available for a given model.
 301 No value means that the effect was not significant. "nb(p,a)" is the number of cases for which 30-yrs and annual means were significantly different from the
 302 reference.

303
 304 Management effect were significant on yield and evapotranspiration for more than half of models irrespectively of
 305 the management set used (Table 3). The effect on drainage was significant only for one of the five models that
 306 provide all three output variables, the LINTUL model. Significant effects were not linked to one management set in
 307 particular, even if they were slightly more frequent in the low fertilization management set (Ms_{F50} , Ms_{F25}) for some
 308 models.

309 3.3 Scaling effect on the 30-year regional means for each management set

310 We analyzed the scaling effect on 30-year regional means by comparing the coarser resolutions to the finest one
 311 for each of the six management sets.

312 **Table 4.** Maximum negative and positive scaling effect among models ($Min(\Delta\bar{X}_S)$; $Max(\Delta\bar{X}_S)$) for each
313 resolution (10 km × 10 km, 25 km × 25 km, 50 km × 50 km and 100 km × 100 km) compared to the finest resolution and
314 number of models in each level of absolute effect ($|\Delta\bar{X}_S|$) for a given output averaged over the region and all 30 years. The
315 results are shown by crop and management set (M_{fix} to Ms_{F25}).

			Wheat						Maize						All crops
			M_{fix}	Ms	Ms_{var}	Ms_{F75}	Ms_{F50}	Ms_{F25}	M_{fix}	Ms	Ms_{var}	Ms_{F75}	Ms_{F50}	Ms_{F25}	All Man
Maximum negative and positive effect (%)	Y ¹	$Min(\Delta\bar{X}_S)$	-9	-8	-12	-8	-10	-15	-11	-9	-11	-8	-7	-11	-15
		$Max(\Delta\bar{X}_S)$	5	24	9	5	6	8	9	10	12	6	7	5	24
	E ²	$Min(\Delta\bar{X}_S)$	-3	-4	-5	-3	-3	-4	-5	-3	-7	-2	-2	-3	-7
		$Max(\Delta\bar{X}_S)$	6	15	7	8	8	6	9	14	7	6	7	5	15
	D ³	$Min(\Delta\bar{X}_S)$	-16	-15	-15	-15	-16	-16							-16
		$Max(\Delta\bar{X}_S)$	0	0	0	0	0	0				NA			0
Number of models by scaling effect level	Y	$ \Delta\bar{X}_S \leq 5\%$	7	6	4	5	4	5	2	4	3	4	4	3	51
		$5\% < \Delta\bar{X}_S \leq 10\%$	4	4	3	4	4	2	4	3	2	2	2	2	36
		$10\% < \Delta\bar{X}_S \leq 15\%$	0	0	2	0	1	2	1	0	2	0	0	1	9
		$20\% < \Delta\bar{X}_S \leq 25\%$	0	1	0	0	0	0	0	0	0	0	0	0	1
		Total	11	11	9	9	9	9	7	7	7	6	6	6	97
	E	$ \Delta\bar{X}_S \leq 5\%$	9	8	7	8	8	8	5	5	4	5	5	5	77
		$5\% < \Delta\bar{X}_S \leq 10\%$	1	1	3	1	1	1	2	1	3	1	1	1	17
		$10\% < \Delta\bar{X}_S \leq 15\%$	0	1	0	0	0	0	0	1	0	0	0	0	2
	Total	10	10	10	9	9	9	7	7	7	6	6	6	96	
	D	$5\% < \Delta\bar{X}_S \leq 10\%$	2	3	4	3	3	3							18
$10\% < \Delta\bar{X}_S \leq 15\%$		1	1	1	1	1	1							6	
$15\% < \Delta\bar{X}_S \leq 20\%$		1	1	0	1	1	1				NA			5	
Total		4	5	5	5	5	5							29	

316 ¹ Y is crop yield

317 ² E is evapotranspiration over the growing season

318 ³ D is drainage over the growing season

319

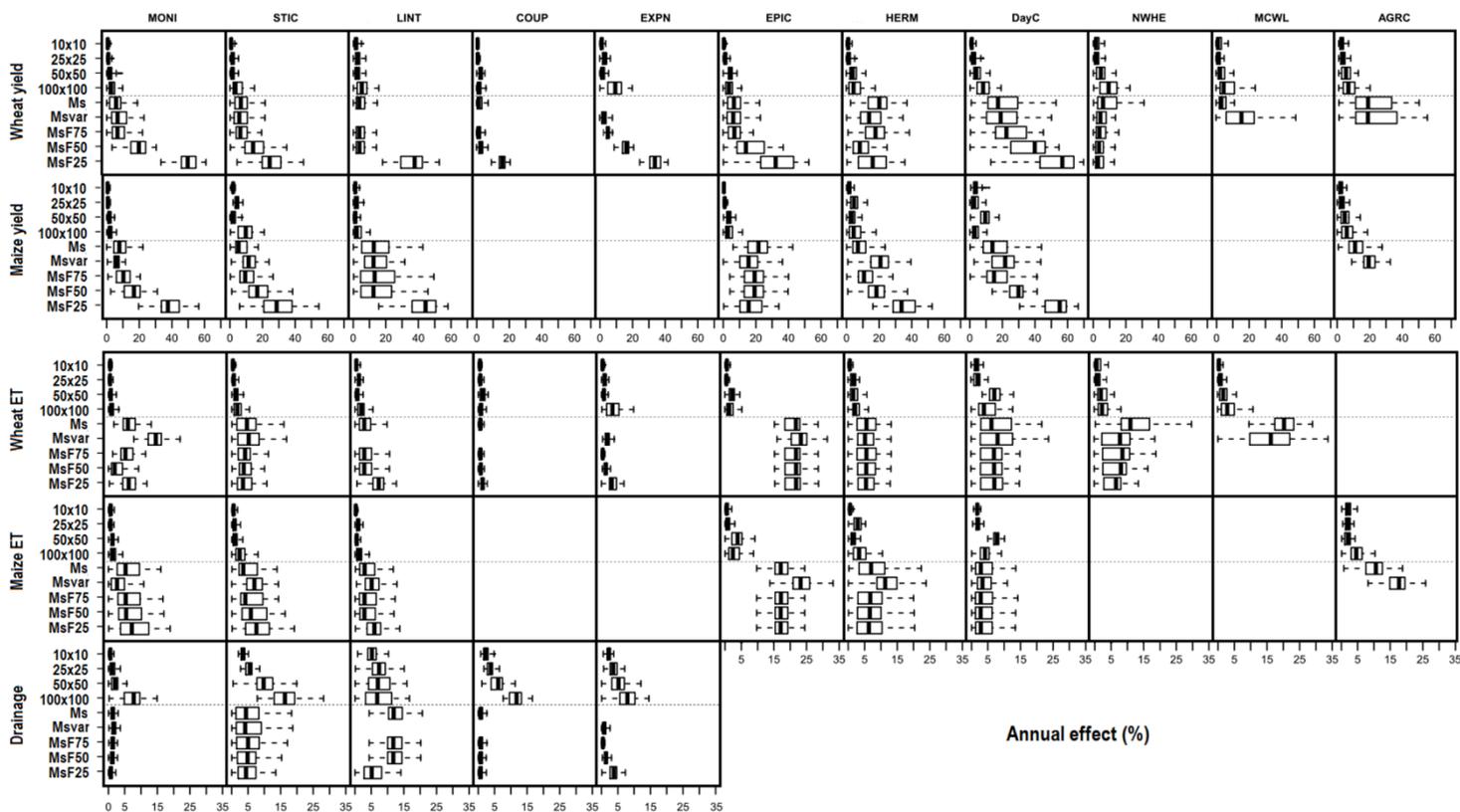
320 Overall, the scaling effect on yield was in a smaller range of differences than the management effect, ranging from
321 -15% to +24% and from -26% to +31%, respectively (Table 2 and 4). The scaling effect was weaker on
322 evapotranspiration than on yield or drainage, with most models having an absolute difference below 5% only. Over
323 all models, the scaling effect was both negative and positive on yield and evapotranspiration but always negative
324 (underestimation) on drainage regardless of the model (Table 4). For the five models simulating the three output
325 variables, evapotranspiration shows the smallest overall range with -5 to 2% while drainage and yield ranged from
326 -16 to 0% and -10 to 3% respectively.

327 Certain models were more sensitive to scaling when simulating maize yield or evapotranspiration, such as STICS,
328 and EPIC, whereas others were more sensitive when simulating wheat, such as LINTUL and DailyDayCent (see
329 Table S2). For models predicting all three outputs, the scaling effect was higher on drainage than on yield and
330 smallest on evapotranspiration. The scaling effect was similar across the management sets, meaning that there is
331 no observable trend related to the management sets, regardless of the crop simulated or model used.

332 The significance was more frequent for management effect than for scaling on yield and evapotranspiration while
 333 it was the opposite for drainage (Table 3). The scaling effect on yield was significant only for the coarsest resolutions
 334 (100×100 km) and for one model (NWHEAT) while it was significant on three models and more resolutions (25×25
 335 km, 50×50 km, and 100×100 km) for evapotranspiration. The scaling effect on drainage was significant for all
 336 resolutions and most models. As opposed to the management effect, the significance of scaling effect was
 337 dependent on resolution with more frequent significant effect for coarser resolutions.

338 3.4 Scaling and management effects at the annual scale

339 For the 30-year simulations, we calculated the ASE and AME on the regional means for each variable and each
 340 model. Compared to AME, ASE was much weaker on yield and evapotranspiration for both crops, particularly when
 341 excluding the 100×100 km resolution (Fig. 4). This effect was more obvious on yield than on evapotranspiration,
 342 for which the ASE and AME often remained weak, which was also the case for simulated drainage. The maximum
 343 difference due to a specific management set or resolution for a given year was also strongly model-dependent.



344 **Figure 4.** Distributions of annual scaling (ASE, 10x10, 25x25, 50x50 and 100x100) and management (AME, Ms, Ms_{var}, Ms_{F75}, Ms_{F50} and
 345 Ms_{F25}) effects on yield, evapotranspiration and drainage over 30-year simulation period compared to their respective reference, for 11 crop
 346 models (without outlier). For a given model, crop and output, each boxplot represents the average over all grid cells for each year over the

347 30 years, and either all management sets for the scaling effect or all resolutions for the management effect. See Table 1 for model
348 abbreviations.

349
350 Figure 4 shows that the maximum ASE was generally small but increased with coarser resolution. For simulated
351 wheat yield, APSIM-Nwheat had highest maximum ASE (77%) compared to the other models (<38%) at the 50×50
352 km resolution due to higher yield using *Ms*, while it was in the same range as those of the other models at the other
353 resolutions. This led to a higher evapotranspiration (28%) as well on this *Ms* set and 50×50 km resolution. Apart
354 from this set, the maximum ASE for APSIM-Nwheat at 50×50 km resolution was 19% and 6% on yield and
355 evapotranspiration, respectively. On maize evapotranspiration, maximum ASE was highest at 25×25 km resolution
356 for HERMES (17%) but was in the same range as those of the other models at the other resolutions (9% or lower).
357 Generally, the models with the highest ASE were APSIM-Nwheat, DailyDayCent, HERMES, and in certain cases
358 MCWLA, STICS, and LINTUL, depending on the output variable and the crop. In general, the ASE on yield of both
359 crops and drainage was similar, and weakest on evapotranspiration (usually less than 10%).

360 The AME was generally higher on yield and evapotranspiration than ASE but had a similar range for drainage.
361 Some models had an extremely large maximum AME, reaching 160% of the difference for a given year on the
362 regional wheat yield for DailyDayCent and 120% on the regional maize yield for LINTUL (Fig. 4). For some models,
363 such as CoupModel, maximum AME was around 10% only, indicating that regardless of the year, the difference
364 due to management was low, except for *Ms_{F25}*, for which the maximum AME was at least 20%, regardless of the
365 model. The AME was weaker on evapotranspiration than on yield and was even weaker on drainage. AME was
366 similar for wheat and maize, but the difference among models was larger for wheat. This is partly because the
367 models with the lowest AME (CoupModel and Expert-N) are available only for wheat and because maximum AME
368 in LINTUL was higher on wheat than on maize evapotranspiration (68-71% vs. 20-25%, respectively). Drainage
369 was less variable, with the weakest AME for the models only simulating all outputs, except for CoupModel, for which
370 the AME was weaker on evapotranspiration. The maximum AME on drainage was 22% for LINTUL, 19% for STICS,
371 11% for Expert-N, 8% for CoupModel, and 4% for MONICA. No consistent trend occurred among the management
372 sets as for evapotranspiration. Additionally, no effect of resolution on AME was observed, since the difference was
373 the same at the five resolutions for a given crop, output variable, and model (data not shown). AME was generally

374 low on evapotranspiration, and even lower on drainage in 90% of the situations, regardless of the model or the crop
375 simulated, unlike regional yield, which was more sensitive to the management set.

376 As for the 30-years averages, significance was more frequent for management effect than for scaling (Table 3).
377 Management influenced significantly yield and evapotranspiration under growing season for some models but not
378 annual drainage. This result was observed for some models simulating the three output variables such as MONICA
379 and STICS that have significant management effect for evapotranspiration or yield but not for drainage. Scaling
380 effects were generally not significant, with some exceptions for the two coarser resolutions while management
381 effects were often significant, especially for the two low fertilization management sets (MS_{F50} and MS_{F25}).
382 Management effects were more frequently significant for maize yield and evapotranspiration than for wheat at this
383 annual scale for most models.

384 **4. Discussion**

385 **4.1. Management and scaling effect on the 30-year regional mean**

386 At the multi-year scale over 30 years, the scaling and management effects were weak for most models, crops and
387 outputs, even if significant. The scaling effect results confirm the results of previous studies on the impact of soil
388 and climate aggregation on yield and net primary productivity (NPP) for the same study site and simulation period
389 (Hoffmann et al., 2016b; Kuhnert et al., 2016). Further, our results indicate that varying management options over
390 space and time in the region did not change the overall findings made when assuming constant management.
391 Nevertheless, the scaling effect depended on the output variable, being larger for drainage than for yield or
392 evapotranspiration when compared between the five models simulating the three output variables. The impact of
393 the choice of the crop (winter or spring crop) on the other hand was negligible. The stronger scaling effect on
394 drainage (observed for models providing the three outputs) and the direction of its difference was probably due to
395 the choice of the dominant soil when moving from high to lower resolution. Lowering the resolution of soil input data
396 resulted in an increase in the total soil water storage because deep soils were dominant in the region, which induced
397 lower drainage. Grosz et al. (2017) also observed the scaling effect on predictions of change in soil organic carbon
398 over time, which depend greatly on soil input data. In the same way, Coucheney et al. (2018) showed that the

399 sensitivity to scaling was output-dependent with a greater effect of soil aggregation on soil C mineralization and N
400 leaching than on yield and drainage for the CoupModel.

401 The maximum management effect tended to be higher than the maximum scaling effect, with 42 vs. 10 % of the
402 cases in which differences compared to the reference were greater than 10 %, respectively. The management
403 effect varied among models, with most 30-year regional mean outputs being slightly sensitive to management
404 (absolute difference below 10%). This was particularly true for evapotranspiration of both crops, drainage and wheat
405 yield, regardless of the input resolution. The stronger effect on yield could be partly due to the use of percentage
406 to quantify the effect. Since average yields are much lower than evapotranspiration and drainage, a small variation
407 lead to a higher percentage for this output. However, for the scaling effect the effect was strongest on drainage.
408 The management effect tended to be higher on maize than on winter wheat yield for most models, suggesting a
409 greater impact of management on spring crops than on winter crops. This result seems consistent with the shorter
410 growing season of spring crops, leaving less time to compensate a late sowing for instance. The hypothesis of a
411 higher sensitivity of spring crops should be tested with other crops such as sunflower or soybean. For some models
412 (2-4 models), different representation of management changed the 30-year regional mean substantially (by more
413 than 15% for yield and for evapotranspiration depending on the resolution and crop), indicating the need to carefully
414 choose how to represent management in these crop models to obtain relevant multi-year regional means. Contrary,
415 management choices seemed less important for the 30-year regional drainage, (showing less than 13 % difference
416 in all management sets).

417 **4.2. Stronger effects at the annual scale**

418 The same trend occurred at the annual scale as for the 30-year regional mean: the management effect was usually
419 higher than the scaling effect, with large differences among models. The management effect as well as the scaling
420 effect on the regional mean were stronger for certain years than for others. This indicates that the choices made to
421 represent management are more important when studies focus on annual regional outputs than on multi-year
422 average regional outputs. This importance varied among models and, depending on the model, the cultivation
423 operation considered. Hereby, it is crucial to ensure that the chosen model is able to predict effects of a given
424 management strategy, such as sowing date, to accurately predict variability in the outputs caused by the

425 management changes. If the management strategy has a substantial effect on the output variable of interest, the
426 uncertainty due to the choice of management option in the simulation should be estimated.

427 Since the years with large effects on management options or scaling differed among models, it is difficult to identify
428 which characteristics of the years that interact with the models to generate the more or less strong effects. No effect
429 of climate characteristics such as a dry or hot year effects was found in the analyses. The effect were strongly
430 model-dependent, the same year predictions being sensitive to scaling or management effect for some models but
431 not for others. No generic characteristics of the input data could be identified; the effect being probably due to a
432 model-soil-climate interaction. This difference between crop model outputs behavior is probably partly due to model
433 structures as well as their parametrization, their the relative contribution being unclear. Hereby, sensitivity analysis
434 performed in individual studies of each model could be helpful to understand model behavior and to determine
435 characteristic input-output relationships (Specka et al., 2015; Varella et al., 2012). It could then clarify the major
436 factors behind model differences with respect to the occurrence of strong effects of management strategies in
437 specific years.

438 **4.3. Representation of management strategies in large-scale studies**

439 We used decision rules to generate management options based on climatic conditions. We then compared
440 simulations based on these management options with those of uniform and fixed sowing, harvest, and fertilization
441 dates over one region over multiple years. In general, uniform sowing, harvest, and fertilization dates as well the
442 use of a single cultivar are an unrealistic representation of common management at the regional scale. Folberth et
443 al. (2016) showed that in model-based global scale assessments, absolute yield levels depend on the
444 parameterization and distribution of crop cultivars. However, it is still commonly applied in large-scale modelling
445 studies since real data are often scarce (Faivre et al., 2004). The advantage of using decision rules is that it provide
446 a management, which is consistent with local climate and soil as compared to fixed assumptions. These can also
447 be used to simulate changes in management over time due to climate change (Senthilkumar et al., 2015). One
448 limitation is that the same decision rules are used for all grid cells, while different farmers apply different rules for
449 crop management (Maton et al., 2005) depending on their social, economic, and pedoclimatic conditions. Decisions
450 rules based on an optimal strategy according to climatic conditions could lead to overestimated yields. Moreover,

451 not taking into account soil characteristics could also lead to unrealistic management in some cases. Since the
452 purpose of this study was to evaluate if management choices had an impact on regional output variables, these
453 concerns were not of critical importance. To get more realistic data on management at large scale, remote sensing
454 could add useful information on crop type (Griffiths et al., 2019), sowing and harvest dates, or irrigation schedules
455 (Battude et al., 2017). Here, we analyzed the potential impact of choosing a variable management to predict the
456 difference in crop model outputs compared to a reference based on a spatially uniform management fixed in time.
457 The access and use of observed management data for the entire region to validate the relevance and accuracy of
458 the decision rules, would improve assessments of the role and effect of management input data and resolution for
459 simulations at regional scale. It could be relevant to include other cultivation operations, such as soil tillage or
460 irrigation, depending on the outputs of interest. For instance, irrigation is important when water balance is the focus
461 of the simulation study, particularly in southern Europe.

462 **5. Conclusion**

463 In our regional-scale study, we showed that the management effect was generally stronger than the scaling effect.
464 The strength of the effects depended on the crop model and the output variable of interest, with some models and
465 output variables being much more sensitive to management options than others. Scaling and management effects
466 were also stronger when evaluated on individual years than on the 30-year mean, for which these effects were
467 usually weak. The effects varied both between models and among years. Strong impacts occurred but not
468 necessarily during the same years for all models, which indicates a need for further analysis with respect to each
469 model to explain these effects in depth. Additionally, the findings of this study might be different in other conditions
470 and therefore need to be confirmed with respect to a different region with contrasting soil and climate conditions.

471

472 **Acknowledgments**

473 This work was supported by the FACCE MACSUR knowledge hub (<http://macsur.eu>). JC, HR, EC and JEB thank
474 the INRA ACCAF metaprogramme for funding. FT and RPR were supported by FACCE MACSUR (3200009600)
475 through the Finnish Ministry of Agriculture and Forestry (MMM). HE, EL and AV were supported by The Swedish
476 Research Council for Environment, Agricultural Sciences and Spatial Planning (220-2007-1218) and by the

477 strategic funding 'Soil-Water-Landscape' from the faculty of Natural Resources and Agricultural Sciences (Swedish
478 University of Agricultural Sciences) and thank professor P-E Jansson (Royal Institute of Technology, Stockholm)
479 for support. ET was funded by the Royal Society of New Zealand and the Climate Change Impacts and Implications
480 for New Zealand project (CCII) financed by the Ministry of Business, Innovation and Employment (MBIE). FE, TG
481 and HH acknowledge support by the German Federal Ministry of Food and Agriculture
482 (BMEL) through the Federal Office for Agriculture and Food (BLE), (2851ERA01J). KCK, CN and XS acknowledge
483 FACCE MACSUR (2812ERA147). MK and JY thank for the funding by the UK BBSRC (BB/N004922/1) and the
484 MAXWELL HPC team of the University of Aberdeen for providing equipment and support through the German
485 Federal Ministry of Food and Agriculture for the DailyDayCent simulations. The funders had no role in study design,
486 data collection and analysis, decision to publish, or preparation of the manuscript.

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669

670 . Supplementary Material

671 **S1.** Minimum and maximum values for management effect for the sets M_s , M_{Svar} and M_{SF75} compared to M_{fix} for a given output, model,
 672 crop and resolution (% difference compared to the reference management set). Brackets contain minimum and maximum differences; a
 673 single value indicates that the minimum equals the maximum. Y is crop yield, E is evapotranspiration over the growing season and D is
 674 drainage over the growing season. See Table 1 for model abbreviations.

		Wheat					Maize					All crops All Res
		1x1	10x10	25x25	50x50	100x100	1x1	10x10	25x25	50x50	100x100	
Y	MONI	[-6;0]	[-5;0]	[-6;0]	[-6;-1]	[-6;0]	[-11;-6]	[-11;-6]	[-11;-6]	[-10;-6]	[-9;-6]	[-11;0]
	STIC	[-5;6]	[-5;5]	[-5;5]	[-4;6]	[-6;4]	[-12;-7]	[-12;-7]	[-12;-7]	[-12;-6]	[-11;-4]	[-12;6]
	LINT	[4;5]	4	4	4	4	[-3;8]	[-3;10]	[-2;11]	[-2;12]	[-2;14]	[-3;14]
	COUP	[1;2]	[1;2]	[1;2]	[1;2]	2	NA	NA	NA	NA	NA	[1;2]
	EXPN	-3	[-5;-2]	[-5;-2]	[-5;-3]	[-5;-4]	NA	NA	NA	NA	NA	[-5;-2]
	EPIC	[-5;4]	[-4;4]	[-4;5]	[-4;5]	[-4;3]	[18;23]	[18;24]	[15;20]	[14;20]	[11;20]	[-5;24]
	HERM	[16;18]	[16;19]	[15;20]	[14;19]	[18;20]	[-18;-5]	[-19;-6]	[-20;1]	[-21;-6]	[-23;-6]	[-23;20]
	DayC	[-16;-2]	[-15;-1]	[-14;0]	[-15;-1]	[-15;1]	[-15;-4]	[-11;-3]	[-11;-2]	[-13;-4]	[-9;0]	[-16;1]
	NWHE	NA	[4;5]	[4;5]	[2;3]	[-1;3]	NA	NA	NA	NA	NA	[-1;3]
	AGRC	[-20;-19]	-18	[-19;-18]	[-19;-17]	[-24;-20]	[-17;12]	[-18;9]	[-19;11]	[-20;12]	[-26;11]	[-26;12]
MCWL	-12	[-7;0]	[-5;4]	[-2;3]	[2;3]	NA	NA	NA	NA	NA	[-12;4]	
E	MONI	[6;14]	[6;14]	[6;14]	[6;15]	[6;15]	[-6;2]	[-5;2]	[-5;3]	[-4;3]	[-4;3]	[-6;15]
	STIC	[2;4]	[3;4]	[3;4]	3	[2;2]	[-7;-6]	[-7;-5]	[-7;-5]	[-7;-4]	[-7;-4]	[-7;4]
	LINT	0	0	0	0	0	[-2;1]	[-2;1]	[-2;2]	[-2;2]	[-2;2]	[-2;2]
	COUP	-1	0	-1	-1	[-1;0]	NA	NA	NA	NA	NA	[-1;0]
	EXPN	0	[-1;0]	[-1;0]	[-2;0]	[-3;0]	NA	NA	NA	NA	NA	[-3;0]
	EPIC	-22	[-23;-22]	[-23;-21]	[-24;-21]	[-24;-22]	[-21;-16]	[-22;-16]	[-23;-17]	[-24;-18]	[-27;-20]	[-27;-16]
	HERM	[-6;-4]	[-5;-4]	[-5;-4]	-4	-3	[-11;-4]	[-10;-3]	[-10;7]	[-11;-2]	[-12;-2]	[-12;7]
	DayC	[-1;3]	[0;3]	[1;3]	[2;3]	[3;4]	[1;4]	[2;4]	[2;4]	[0;2]	[-1;3]	[-1;4]
	NWHE	NA	9	10	[9;26]	[8;10]	NA	NA	NA	NA	NA	[0;26]
	AGRC	NA	NA	NA	NA	NA	[-17;-11]	[-16;-12]	[-16;-9]	[-16;-9]	[-19;-9]	[-19;-9]
MCWL	[-6;-6]	[0;14]	[15;21]	[15;20]	[16;18]	NA	NA	NA	NA	NA	[-6;21]	
D	MONI	[-2;-1]	[-2;-1]	[-2;-1]	[-2;-1]	-2						[-2;-1]
	STIC	[-5;-4]	[-5;-4]	[-5;-4]	[-5;-4]	-4						[-5;-4]
	LINT	[-12;-11]	-12	-12	-12	-12			NA			[-12;-11]
	COUP	-1	-1	-1	-1	-1						-1
	EXPN	0	[-2;0]	[0;1]	[0;1]	[0;1]						[-2;1]

675

676 **S2.** Minimum and maximum values for scaling effect between all resolutions compared to the reference resolution (1 km × 1 km in most
677 cases) for a given output, model, management set and crop (% difference compared to the reference resolution). Brackets contain
678 minimum and maximum values; a single value indicates that the minimum equals the maximum. Y is crop yield, E is evapotranspiration
679 over the growing season and D is drainage over the growing season. See Table 1 for model abbreviations.

		Wheat					Maize					All crops		
		<i>M_{fix}</i>	<i>M_s</i>	<i>M_{s_{var}}</i>	<i>M_{s_{F75}}</i>	<i>M_{s_{F50}}</i>	<i>M_{s_{F25}}</i>	<i>M_{fix}</i>	<i>M_s</i>	<i>M_{s_{var}}</i>	<i>M_{s_{F75}}</i>		<i>M_{s_{F50}}</i>	<i>M_{s_{F25}}</i>
Y	MONI	[0;1]	[0;1]	[0;2]	[0;1]	[0;2]	[0;2]	[-1;0]	[0;1]	0	[0;1]	[0;2]	[0;2]	[-1;2]
	STIC	[-4;1]	[-5;1]	[-6;-1]	[-5;1]	[-4;2]	[-3;2]	[-11;-2]	[-9;-1]	[-11;-2]	[-8;-1]	[-7;-1]	[-7;-1]	[-11;2]
	LINT	[-5;-2]	[-6;-2]	NA	[-5;-2]	[-5;-2]	[-5;-2]	[-6;-3]	[-1;0]	[-5;-2]	[-1;0]	[-1;0]	[-1;0]	[-6;0]
	COUP	[-1;2]	[-1;3]	NA	[-1;3]	[-1;3]	[-1;3]	NA	NA	NA	NA	NA	NA	[-1;3]
	EXPN	NA	[-8;-1]	[-10;-2]	[-8;-1]	[-8;-1]	[-8;0]	NA	NA	NA	NA	NA	NA	[-10;0]
	EPIC	[-1;4]	[0;5]	[-1;4]	[-1;5]	[-2;4]	[-3;5]	[-1;6]	[-1;3]	[-1;3]	[-1;3]	[-1;3]	[-1;3]	[-3;6]
	HERM	[-1;3]	[-1;4]	[-3;0]	[0;4]	[0;6]	[0;8]	[-3;3]	[-4;4]	[-9;0]	[-4;2]	[-5;3]	[-5;5]	[-9;8]
	DayC	[-9;0]	[-5;3]	[-6;2]	[-8;2]	[-10;3]	[-15;0]	[-5;9]	[-1;10]	[1;12]	[-4;6]	[-2;7]	[-11;2]	[-15;12]
	NWHE	[-7;-1]	[-8;24]	[-12;1]	[-8;0]	[-9;-1]	[-12;-5]	NA	NA	NA	NA	NA	NA	[-12;24]
	AGRC	[1;5]	[3;7]	[-2;3]	NA	NA	NA	[2;6]	[0;6]	[-10;2]	NA	NA	NA	[-10;7]
MCWL	[-3;0]	[-4;0]	[2;9]	NA	NA	NA	NA	NA	NA	NA	NA	NA	[-4;9]	
E	MONI	0	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]	[-1;0]	[0;1]	0	1	1	[1;2]	[-1;2]
	STIC	[0;1]	[0;1]	[-2;0]	[0;1]	[0;2]	[0;2]	[-4;-1]	[-2;1]	[-4;0]	[-2;1]	[-1;1]	[-1;1]	[-4;2]
	LINT	[-2;0]	[-2;1]	NA	[-2;0]	[-2;0]	[-1;0]	[-2;0]	[-1;0]	[-2;0]	[-1;0]	[-1;0]	[0;1]	[-2;1]
	COUP	[-1;1]	[0;1]	NA	[0;1]	[0;1]	[0;1]	NA	NA	NA	NA	NA	NA	[-1;1]
	EXPN	NA	[-3;0]	[-5;-1]	[-3;0]	[-3;0]	[-2;1]	NA	NA	NA	NA	NA	NA	[-5;1]
	EPIC	[-1;2]	[-1;3]	[-3;0]	[-1;3]	[-1;3]	[-1;3]	[0;6]	[0;4]	[-2;1]	[0;4]	[0;4]	[0;4]	[-3;6]
	HERM	[-1;1]	[1;2]	[0;1]	[1;2]	[1;2]	[0;2]	[-4;1]	[-2;14]	[-6;2]	[-2;3]	[-2;3]	[-3;3]	[-6;14]
	DayC	[1;6]	[2;8]	[1;7]	[2;8]	[2;8]	[0;6]	[1;9]	[2;7]	[2;7]	[0;6]	[2;7]	[0;5]	[0;9]
	NWHE	[-2;-1]	[-2;15]	[-4;0]	[-2;0]	[-3;-1]	[-4;-2]	NA	NA	NA	NA	NA	NA	[-4;15]
	AGRC	NA	NA	NA	NA	NA	NA	[-5;-2]	[-3;0]	[-7;-1]	NA	NA	NA	[-7;0]
MCWL	[-1;1]	[-4;0]	[0;2]	NA	NA	NA	NA	NA	NA	NA	NA	NA	[-4;2]	
D	MONI	[-6;0]	[-7;0]	[-7;0]	[-7;0]	[-7;0]	[-7;0]						[-7;0]	
	STIC	[-16;-3]	[-15;-3]	[-15;-3]	[-15;-3]	[-16;-3]	[-16;-3]						[-16;-3]	
	LINT	[-6;-4]	[-6;-4]	NA	[-7;-5]	[-7;-5]	[-7;-5]						[-7;-4]	
	COUP	[-11;-2]	[-12;-2]	NA	[-12;-2]	[-12;-2]	[-12;-2]			NA			[-12;-2]	
	EXPN	NA	[-8;-2]	[-7;-2]	[-8;-2]	[-8;-2]	[-9;-2]						[-9;-2]	

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